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Landsat study of deforestation in the Amazon region of Colombia: Departments of Caquetá and Putumayo

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ABSTRACT

The Amazon rainforest, the largest in the world in terms of size and diversity, is recognized as a source of ecological services for both local and worldwide communities. Ten percent of its territory belongs to Colombia, covering approximately 35% of the country's total area. In spite of global efforts, it continues to be vulnerable to deforestation pressures. In the departments of Caquetá and Putumayo, human activities such as logging and cattle ranching are the main causes of deforestation, which is increasing the department's vulnerability to climate change and natural hazards. However, there is a lack of consistent quantitative monitoring in the Colombian Amazon region, not only of total deforestation rates but also of specific locations and causes of deforestation, despite its high rates of deforestation compared to neighboring Ecuador. In this study, Landsat 7 ETM+ and Landsat 8 images over a sixteen-year period were used to map recent changes in land cover in the departments affected by deforestation. Supervised classifications were made using the Maximum Likelihood Classifier (MLC) and expert classification system, using False Color IR composites which were effective for identifying vegetation land cover. Over sixteen years, the Tropical Rainforest land cover in the study region lost 5.2% of its area, corresponding to 3020.56 square kilometers. Overall, the study region shows an annual rate of deforestation of 0.46%, and for Caquetá alone that rate is 0.77% - about twice as high as estimates from previous studies of between 0.38% and 0.4% loss rates for tropical South America. No single factor driving deforestation was found; rather, different regions within the study area displayed different rates and causes. The particularly rapid deforestation in the department of Caquetá and the encroachment of agricultural activities into national park reserves may be explained by higher colonization pressures and intensification of illegal coca cultivation.

1. Introduction

The world's largest tropical rainforests are found in Asia, Central Africa, and Amazonia, covering about 12% of Earth's land surface (excluding ice-covered areas such as Antarctica) (Boucher et al., 2011). Approximately 20% of this area was used as pasture or cropland in 2000 (Ramankutty et al., 2008), not including land that had been previously farmed but subsequently abandoned (Boucher et al., 2011). While there are still vast areas of undisturbed rainforest, these are being threatened by ongoing transformation, reducing habitats and the resources they provide (Lewis et al., 2015). Even though the rate of expansion of agricultural lands has slowed since 1960 and tropical regions have shown overall net increases in forest cover between 2001 and 2010 (Chazdon and Guariguata, 2016), rapid deforestation is still occurring in some tropical countries and the location and extent of deforestation as well as its impact on important ecosystem services such as biodiversity, climate regulation, carbon storage, and water supplies, are still not well understood (Etter et al., 2006c; Hansen et al., 2013). Studies assessing tropical forest cover change and its causes have been done in tropical regions (Grinand et al., 2013; Hansen et al., 2009; Kim et al., 2015; Margono et al., 2012), however, international coordination of resources to increase capacity, repeated coverage of tropical forests, access to quality updated data and standardized protocols for data interpretation and analysis are still needed (Achard et al., 2007), and some regions continue to receive more attention than others.

The Amazon rainforest is the world's largest rainforest and plays a key role as a carbon sink that controls the entire planet's atmospheric carbon levels, storing more than ten times the annual global emissions from fossil fuels ("Amazon Rainforest, ", 2015). Despite its importance, increased anthropogenic pressure encroaching into the amazon associated with population growth and high rates of migration (referred to as colonization) have been shown to be affecting the region (Perz et al., 2005). Environmental factors including geology, topography, and soil quality, climatic factors such as drought, and economic factors related

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to infrastructure and road development all contribute to deforestation; however, population pressures and shifting cultivation are often the main factors behind deforestation (Armenteras et al., 2013a).

Joint actions among institutions are therefore required in order to slow the pace of deforestation, and private companies and communities need to agree on strategies for reducing deforestation and conserving biodiversity (Leonel, 2016). The Colombian Restoration Plan (Ministerio de Ambiente y Desarrollo Sostenible, 2015) is a good example of such an effort. However, in order to be able to implement this type of strategy effectively, there needs to be not only an accurate and ongoing quantification of deforestation rates, but a clear identification of its causes, and this in turn requires an analysis of the types and distribution of the land cover changes taking place. The differences in deforestation rates observed in neighboring countries within the same region suggests that the causes are complex, and related not only to the suitability of the climate and soil for activities such as agriculture and livestock farming, but also to the specific social, economic and political conditions of the region. Colombia, for instance, has spent 60 years in an internal armed conflict, which has disproportionately affected certain areas including Putumayo and Caquetá. Illicit crops and logging are widespread in the region, but violence and insecurity has made monitoring and control of land use nearly impossible.

The Food and Agriculture Organization of the United Nations (FAO) has been evaluating global changes in forest extension and distribution since 1947; however, their estimates of forest cover and deforestation have been criticized as being unreliable, in part because they depend on national surveys and models (Grainger, 1996). Remote Sensing is increasingly used to improve these estimates; however, results may not be publicly available, techniques are not always consistent from region to region, and there are disagreements on the classification of different forests. These studies also tend to underestimate rates of deforestation because they measure only net forest cover, and do not consider that destruction of natural forests is partially offset by plantation, e.g. Matthews (2001).

Landsat has been used extensively to study deforestation in the Brazilian Amazon basin (Alves, 2002; Alves et al., 2009; Bewernick et al., 2015; Guild et al., 2004; Li et al., 2011; Lu et al., 2013; Shimabukuro et al., 2000; Souza et al., 2013), in the Ecuadorian Andean Amazon (Curatola Fernández et al., 2015; Santos et al., 2017), the Bolivian Amazon (Locklin and Haack, 2003; Marsik et al., 2011) and the Peruvian Amazon (Oliveira et al., 2007; Salovaara et al., 2005), and other sensors with higher resolutions such as SPOT have been used within the Brazilian territory (Carreiras et al., 2006; Lu et al., 2012; Souza et al., 2003). The use of Landsat data for documenting trends in deforestation was crucial to Brazil's conservation policy formulation and implementation, and Brazil is the only country to date that produces and shares detailed spatial information of annual forest extent and change (Hansen et al., 2013).

While some deforestation studies have been done using remote sensing in Colombia, most are local studies in individual municipalities that do not specify what type of land use has replaced the forests (Zuleta, 2015). Evidence shows that half of the Colombian Amazon is experiencing high rates of deforestation (Ruiz, 1989; Sierra, 2000); substantially higher, in fact, than those found in the rest of the Amazon (Armenteras et al., 2006). However, there are no updated regional geographic databases documenting the dynamics and patterns of land cover change and fragmentation in this region (Sierra, 2000).

Deforestation in the department of Putumayo started during the last century, and previous satellite change detection analysis has shown that the annual rates of deforestation are considerably higher on the Colombian side of the border with Ecuador (Viña et al., 2004). This disproportionate rise in deforestation greatly increases the vulnerability of the department to negative impacts including floods, erosion, loss of essential ecosystems, displacement, and loss of cultural identity, among others (Gobernación del Putumayo, 2016). Given this fact, the absence of previous systematic deforestation studies in the department of Putumayo is surprising.

Complex environmental conflicts mostly associated with land use, expansion of the agricultural frontier, livestock, illegal mining, forest fires, illicit crops, infrastructure expansion, urbanization and extraction of wood has caused habitat fragmentation, reduction in the quantity and quality of water supply and loss of biodiversity in the department of Caquetá. Although a large fraction of the department is located within a forest reserve area, illegal mining and quarrying, and uncontrolled construction activities and road improvements are currently affecting water and natural resources, causing erosion and landslides (Gobernación del Caquetá, 2016). Moreover, as deforestation progresses, the forest structure in remaining vegetation patches further degrades (Rocha-Santos et al., 2016).

In order to update information from studies done in previous decades in the Colombian Amazon (Armenteras et al., 2013b, 2006; Etter et al., 2006a; Grainger, 1996; IDEAM, 2002; Linares et al., 2007; Riaño Umbarila et al., 2007; Ruiz et al., 2011) and to better understand the drivers of deforestation, systematic analysis of local-scale land use and land cover (LULC) changes must be performed, region by region (Lambin et al., 2003). Here we provide such an analysis for the departments of Caquetá and Putumayo within the Amazon region of Colombia, focusing on changes occurring between 2000 and 2016, using Landsat images to quantify LULC changes. Our results are then used to identify the biophysical and socioeconomic factors specific to the region that may explain these changes.

2. Materials and methods

2.1. Study Area

We chose as our study area a large subset of the Colombian Amazon corresponding to the departments of Caquetá and Putumayo (see Fig. 1), both of which are strongly affected by human activity.

The department of Putumayo is located in the south of Colombia, bordered to the south by Ecuador and Peru and to the north by the department of Caquetá. Putumayo has two morphological units: the west flank of the Eastern mountain range that extends to the Amazonian foothills; and the Amazonian plain. (“Gobernación de Putumayo, ”, 2017). The department of Caquetá is located immediately to the north of Putumayo, and consists of three well-defined morphological units: the eastern flank of the Eastern mountain range, the foothills, and the Amazon plain (“Gobernación de Caquetá, ”, 2017).

The entire study area has a tropical rainforest climate according to the updated Koppen-Geiger classification (Peel et al., 2007). Based on data provided by the Institute of Hydrology, Meteorology and Environmental Studies (IDEAM), the area has a total precipitation of 3235 mm per year with an average temperature of 25.11 °C (IDEAM, 2014). Although there is rainfall throughout the year, “ecological summer" seasons can be defined in which the monthly rainfall is below average; similarly an "ecological winter" season in which the volume of rainfall is higher than the monthly average (”Corpoamazonia, ”, 2013). In this unimodal regime (Fig. 2), seasonality is important since the phenology of the vegetation could affect the LULC patterns of an area (Jia et al., 2017).

2.2. Data acquisition and image pre-processing

The prevalence of clouds in the tropics makes data selection challenging regardless of satellite data resolution. Hence, finding an appropriate Landsat scene for a large area of interest (AOI) is especially difficult and sometimes impossible (Knudby et al., 2014). We were able to find five suitable pairs of Landsat satellite scenes covering the study area, courtesy of the U.S. Geological Survey, covering the period from 2000 to 2016. Features of these scenes are shown Table 1.

Even during the ecological summer season, some cloud coverage is constantly present in the region, especially in the areas closest to the

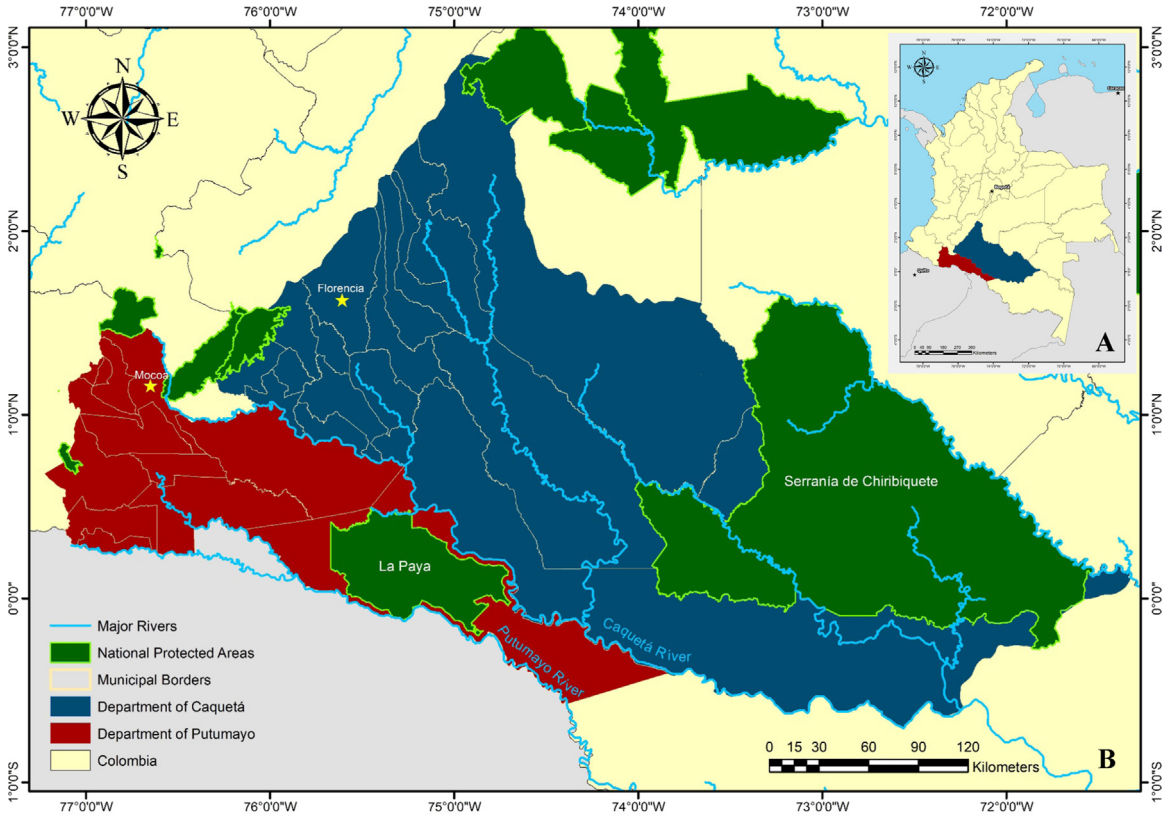

Fig. 1. Location map of the study area. (A) Map of Colombia showing Caquetá (blue) and Putumayo (red) (B) Zoom of the study area with national protected areas shown in green.

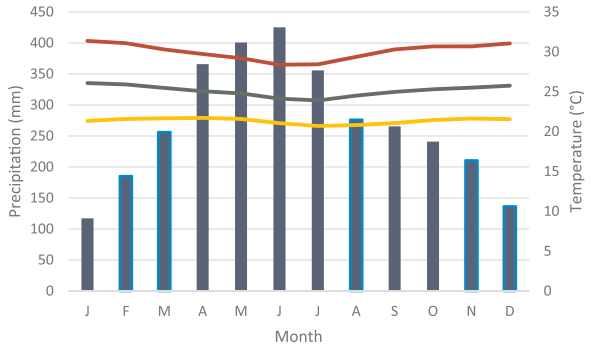

Fig. 2. Histogram of precipitation amounts (blue bars), maximum temperature (red line), average temperature (green line) and minimum temperature (yellow line). Bars highlighted in light blue indicate months in which Landsat scenes were acquired.

Table 1
Satellite data specifications showing characteristics of the chosen Landsat scenes, including path and row, date of acquisition and percentage of cloud cover for each period.

Data	Landsat 7 ETM +		Landsat 8	
Year	2000		2016	
Path/Row	Date of acquisition	Cloud Cover (%)	Date of acquisition	Cloud Cover (%)
7/60	December 13	2.00	February 01	0.28
8/60	August 30	0.00	March 11	16.52
8/59	August 30	7.00	March 11	11.07
9/59	November 09	28.00	August 09	46.78
9/60	November 09	13.00	August 09	61.23

west flank of the eastern ranges. The AOI did not have sufficient temporal stability to apply a multi-scene ensemble classification approach as done by Knudby et al. (2014) in the absence of cloud-free scenes. For this reason, our methodology makes use of subset images created to emphasize the Amazonian plain morphological unit and to omit areas heavily affected by cloud coverage. A total of ten subset images were created (Fig. 3), five for each period. The remaining cloud presence was partially mitigated through atmospheric corrections using the ATCOR-2 atmospheric correction tool® for haze removal, as suggested by Song et al. (2001); the QA band for cloud mask; and Surface Reflectance data. Image processing was performed using ERDAS Imagine 14 and ArcGIS 10.5.

2.3. Image classification

Supervised image classifications were applied to the 2000 and 2016 subset images using the Maximum Likelihood Classification algorithm (MLC). The MLC approach was applied because it has been successfully used for previous Landsat classifications in the region (Etter et al., 2006b; Messina and Delamater, 2006; Reyes, 2017). For the supervised classification, nine Level I classes were defined for both periods according to spectral variations of the same LULC category. The classification scheme was based on the land cover and land use classification system developed by Anderson (1976) and defined according to the land features present in the region (Table 2).

A False Color IR composite, which is the standard technique for visual interpretation in tropical forest mapping was used because it provides a clear differentiation of the LULC categories (Duadze, 2004). The sampling scheme for the MLC proposed by Li et al. (2014) was applied to each subset image: polygons were drawn around representative sites for each category in order to define their respective spectral signatures. Mixed pixels are a common problem when using data with medium spatial resolution such as that of Landsat, especially

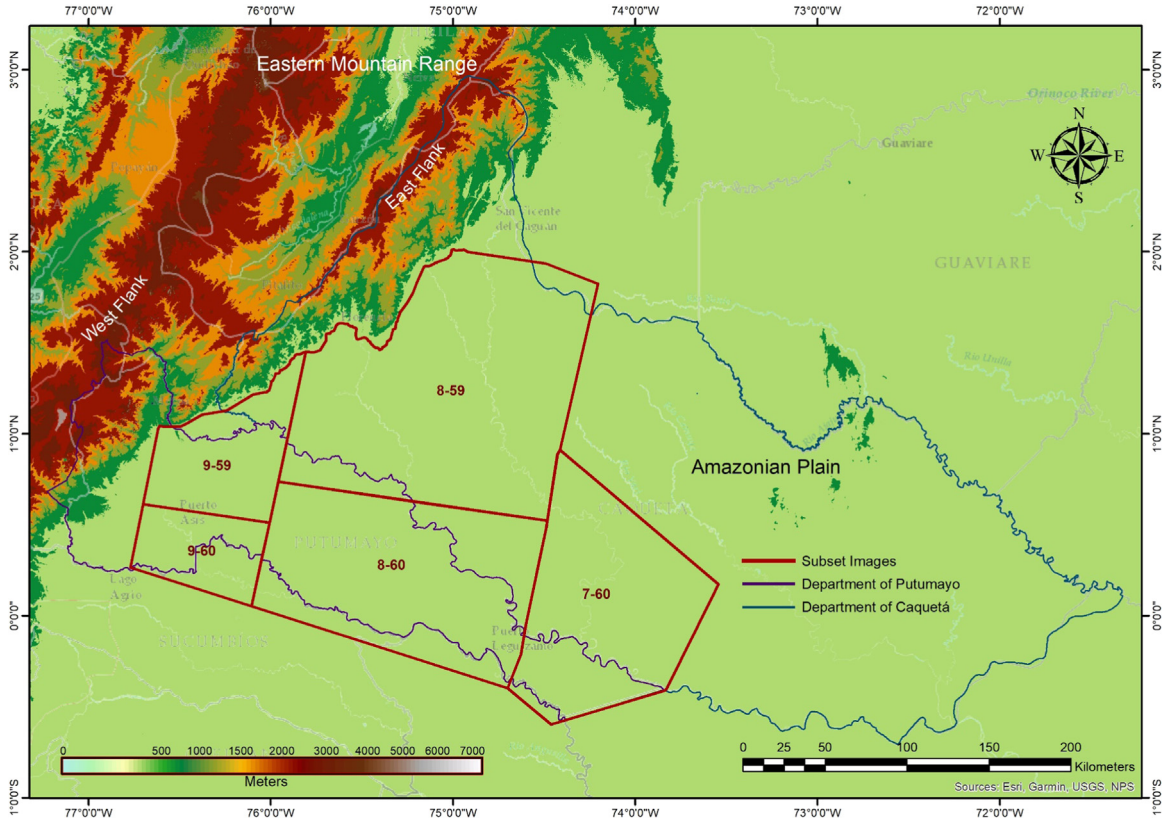

Fig. 3. Map showing the delineation of the subset images with a Shuttle Topography Radar Mission (SRTM) digital elevation model as background and a World Terrain Reference Overlay basemap.

Table 2
Land use and land cover classification scheme.

LULC class	Description
Tropical Rainforest	Land covered by dense Amazon rainforest
Rangeland	Natural vegetation, predominantly grasses, grass-like plants, forbs, or shrubs
Agriculture	Crop fields, bare fields and pasture
Water	Streams, river, lakes, ponds and reservoirs
Soil	Land areas of exposed soil
Barren Land	Sand, rock and barren area influenced by human activity
Built-Up	Residential, commercial, industrial, and mixed urban areas
Clouds	Areas covered by clouds
Shadows	Areas shaded by clouds

in urban areas which have a heterogeneous mix of features including buildings, grass, roads, soil, vegetation and water (Butt et al., 2015). To improve classification accuracy, the problem of mixed pixels was addressed by visual interpretation supported by Google Earth.

Persistent atmospheric effects and similarities in the spectral responses of some classes caused noisy LULC maps, so we used the ERDAS Knowledge Engineer to apply an expert classification system model based on hierarchical user-defined decision rules in order to reduce classification errors (Geosystems, 2005). Using individual band values and the Normalized Difference Vegetation Index (NDVI), the misclassified pixels resulting from the initial classification were re-evaluated and properly reclassified, then confirmed using visual interpretation and false color composites. Finally, a neighborhood 3 × 3 majority function was applied to each classification in order to recode isolated pixels (Yuan et al., 2005) and reduce the salt-and-pepper effect. An example of the post-classification enhancement process is shown in Fig. 4. Through the expert system, misclassifications related to atmospheric interference were corrected and the LULC classification improved significantly until it reached the desired accuracy according to Anderson (1976).

2.4. LULC change detection

Multi-temporal satellite imagery is routinely used to detect and monitor changes in ecosystems, and maps of land cover evolution are produced by comparing a pair of classified images from two different time periods (Coppin et al., 2004). We used the Post-Classification Comparison (PCC) change extraction algorithm to compare the classified pairs of images from 2000 and 2016. Change maps are subject to the same errors as the input classifications (Hecheltjen et al., 2014), so we used a pixel-by-pixel comparison of the LULC maps to produce a change matrix showing quantitative “from-to” changes. These changes can be also displayed visually as a change detection map, which facilitates the interpretation (Rawat and Kumar, 2015). Cross-tabulation analysis simplifies the calculation of the quantity of conversions from one LULC class to another, and their corresponding areas, over the period evaluated (Dewan and Yamaguchi, 2009).

2.5. Accuracy assessment

The level of accuracy that can be obtained in LULC maps depends on the level of classification employed, the scale of the area and the spatial resolution of the imagery used in the analysis (Stabursvik, 2007). In this study, the accuracy assessment was performed using a stratified random sampling for the LULC maps of both periods as well as for the change detection map. A minimum of 50 sample points for each category were considered, as recommended by Manandhar et al. (2009). A total of 1500 sampling points were used for each LULC map and 500 sampling points for the change detection map to derive the accuracies. The Kappa coefficient, often used as an overall measure of accuracy (Congalton, 2004), was not used in this study as its suitability has been questioned

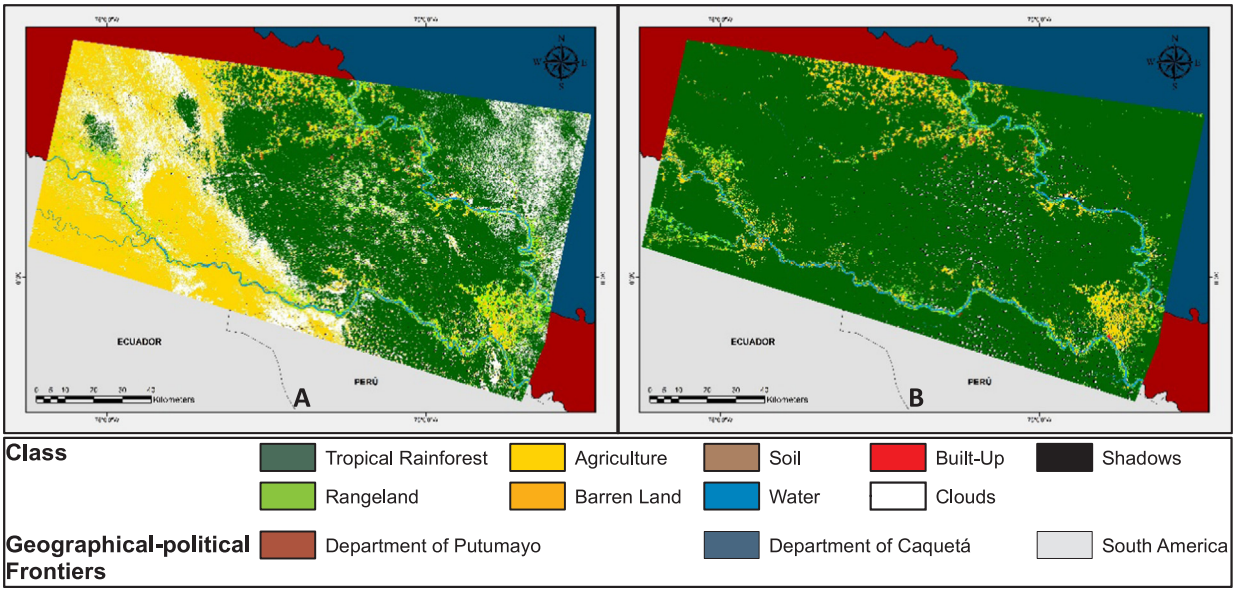

Fig. 4. Comparison of image classification results for the 2016 Path 8 Row 60 subset image. (A) Initial supervised Maximum Likelihood Classification (B) Expert system post-classification results.

because of its use of randomness as a baseline (Olofsson et al., 2013; Pontius and Millones, 2011). Instead, an error-adjusted estimator of area was produced after the accuracy assessment was performed, in order to calculate confidence intervals for the areas of land change.

3. Results and discussion

3.1. Supervised classification

The MLC using the False Color IR band combination resulted in a very good separability between Tropical Rainforest and Agriculture from other LULC categories. The Landsat 8 coastal aerosol band was especially useful for assessing and correcting errors caused by clouds and atmospheric interference, but could only be applied to the 2016 scenes. For the 2000 scenes a combination of various band values was used to perform a similar correction. For both periods the short-wave and thermal infrared bands as well as the NDVI were useful for differentiating between types of vegetation cover. Nonetheless, there was no general rule that could be applied to all supervised classifications with the expert system; each scene had its own specific suitable bands and NDVI values that allowed the separability among LULC categories to be improved.

LULC maps (Fig. 5) and statistics were produced for both periods, and the total (and percent) areas covered by each LULC category are summarized in Table 3.

Overall there was a substantial decrease in the Tropical Rainforest cover together with a reduction in Rangeland and Soil. Tropical Rainforest land cover presented the largest decrease in area, losing 3020.56 square kilometers over sixteen years, which corresponds to a 5.2% reduction of its original coverage. An average annual deforestation rate of change of 0.46%, calculated as suggested by Abbas et al. (2016), was obtained for the entire area of study. Rangeland and Soil areas decreased by 893.18 and 310.25 square kilometers respectively. Agriculture showed a large increase of 7.32%, equivalent to 4260.10 square kilometers, whereas Built-Up and Barren Land increased by only 5.50 and 80.23 square kilometers respectively (Table 3).

Looking at the LULC vegetation categories separately for the each department (Table 4), it can be seen that the Department of Caquetá experienced higher deforestation than the average overall in both departments, losing 7.95% of the Tropical Rainforest land cover over the sixteen-year study period, an average rate of 0.77% per year. Rangeland also showed a decrease of 1.03%, while Agriculture increased by 10.02%. On the other hand, the Department of Putumayo showed a decrease of 2.5% in Rangeland, while Agriculture increased by 2.11%, and Tropical Rainforest increased only by 0.14%.

Even though in the central and eastern municipalities of Putumayo agricultural activities clearly increased (although not as substantially as in Caquetá), the western municipalities of the department showed the opposite trend: a decrease in Agriculture and an increase in Tropical Rainforest was observed. Since no reforestation projects have been carried out in either of the departments that could explain the slight increase of Tropical Rainforest land cover in the western region of the Department of Putumayo, it is likely due to the periodicity of extractivism and to the fact that the agricultural frontier is now expanding further into the Amazon forest, where resources have not yet been depleted or overexploited. Additionally, some portion of the forest area increase may be explained by the rainfall seasonality between months. When comparing this information with the average rainfall data of the IDEAM, it is evident that the highest deforestation rate is observed in the driest seasons of the year, and the higher precipitation rates during the rainy season may have resulted in the apparent increase of vegetation in some areas. However, it is clear that the conversion of forest to agriculture cannot be explained by seasonality. The apparent stability in overall Tropical Rainforest cover in Putumayo can therefore be explained by the fact that deforestation in one area has been offset by reforestation in another.

Consequently, even though the AOI as a whole showed a large decrease of the Tropical Rainforest land cover and an increase in Agriculture (Figs. 5 and 6), it can be seen that each department, and even the municipalities within them, have been affected differently throughout the period of study. This is consistent with the national trends described by Armenteras et al. (2013a), confirming that the process of deforestation in Colombia is not homogeneous, but rather has a high spatial variability within the country in terms of both the rate and the causes of deforestation, even in neighboring departments within the same region which share agriculture types and national deforestation policies.

3.2. Land use and land cover change detection

In the departments of Putumayo and Caquetá, a total of 6382.68 km^2 of Tropical Rainforest land was converted into other LULC

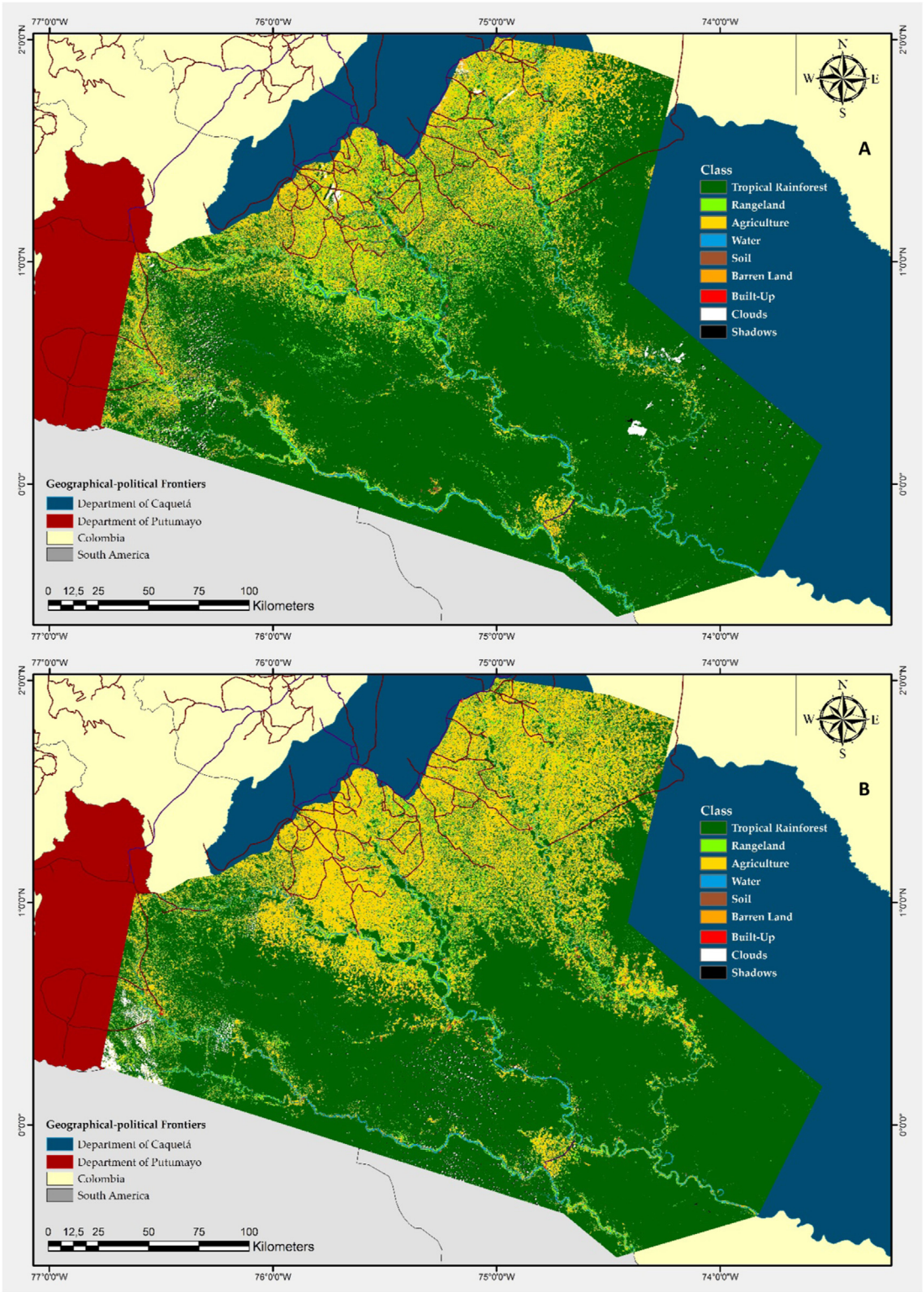

Fig. 5. Land use/Land cover maps of the area with the road network - earthen/rural roads (dark red) and paved roads (purple). Supervised classification results: (A) LULC map for the year 2000 (B) LULC map for the year 2016.

categories, of which 4641.76 km^2 were converted into Agriculture. A total of 6636.10 km^2 of new land use for Agriculture was established. However, 35,463.57 km^2 of Tropical Rainforest remained unchanged. The complete "from – to" change information is presented in Table 5. Cloud and Shadow land cover categories were not included in the change detection analysis.

The most severe LULC changes occurred in the Department of Caquetá mainly along the rivers and the colonization front. In the Department of Caquetá, a high population growth rate (according to the statistics of the National Administrative Department of Statistics (DANE)) caused the colonization front to advance in an easterly direction into to the Amazon. In this area, the main cause of deforestation is the conversion of forest to pastures to expand livestock production and commercial agriculture, rather than illegal coca cultivation

Table 3
LULC categories total coverage in terms of area and percentage for both periods, as well as the difference (Δ) between them expressed in percentage gain (+) and loss (-).

	2000		2016		Δ
	km^2	%	km^2	%	%
Tropical Rainforest	42,244.52	72.59	39,223.96	67.40	− 5.19
Rangeland	3813.48	6.55	2920.30	5.02	− 1.53
Agriculture	9658.07	16.60	13,918.16	23.92	7.32
Water	930.53	1.60	794.36	1.37	− 0.23
Soil	734.45	1.26	424.20	0.73	− 0.53
Barren Land	193.34	0.33	273.58	0.47	0.14
Built-Up	10.12	0.02	15.64	0.03	0.01
Clouds	390.52	0.67	496.58	0.85	0.18
Shadows	219.94	0.38	127.72	0.22	− 0.16

Table 4
Total area coverage of vegetation categories in km^2 for each department in both periods.

	Department of Caquetá		Department of Putumayo	
	2000	**2016**	**2000**	**2016**
Tropical Rainforest	26,324.25	23,275.51	15,920.26	15,948.45
Rangeland	2620.55	2224.49	1192.93	695.81
Agriculture	7771.33	11,611.85	1886.73	2306.31

(Dávalos et al., 2016). Along with livestock production, the potential to expand oil palm plantations poses a threat to the area's forests, because Caquetá is highly suitable for plantation development. Deforestation patterns along rivers and colonization fronts in Caquetá are clearly different from the "fishbone" patterns observed in the Brazilian Amazonia and Ecuador (Sierra, 2000), where the construction of roads is one of the main drivers of deforestation (e.g. Batistella et al., 2000), a determinant that is not apparent yet in the Colombian Amazon. The observed deforestation is not associated with the any major road construction, but it is possible that the earthen/rural road network has expanded together with the agricultural development. However, Landsat's resolution is too coarse to include roads as a separate land cover category because most are narrow earthen and rural roads, and there are no major paved roads in the area

In contrast, in the southern section of the study area which corresponds mainly to the Department of Putumayo, agriculture seems to be migrating from the western municipalities to the central and eastern ones, encroaching further into the Amazon. Most of the Tropical Rainforest is preserved, even where there are no delineated preservation zones such as natural parks, with the exception of a few areas along the rivers and near the major urban settlements. However, the evidence of deforestation in protected areas is worrisome: the national natural park of La Paya in Putumayo lost 90.42 square kilometers of its Tropical Rainforest. The La Paya deforestation is located mainly along the Mecaya and Sensella rivers to the north, and to the east near Puerto Leguízamo due to agricultural growth. This is significant because while much attention is directed towards understanding the patterns of biodiversity, much less is given to determining the areas most vulnerable to threats (Wilson et al., 2005).

Biophysical events occasionally generate further changes, because of the combination of increased soil erosion and increased population: landslides and floods are the two main natural hazards faced by the Department of Putumayo. Floods represent the greatest threat to the department, with 5% of the territory subjected to periodic flooding according to the National Planning Department. The flood threat is concentrated along the main water bodies, particularly along the rivers of Putumayo and Caquetá. This happens to coincide with the areas that

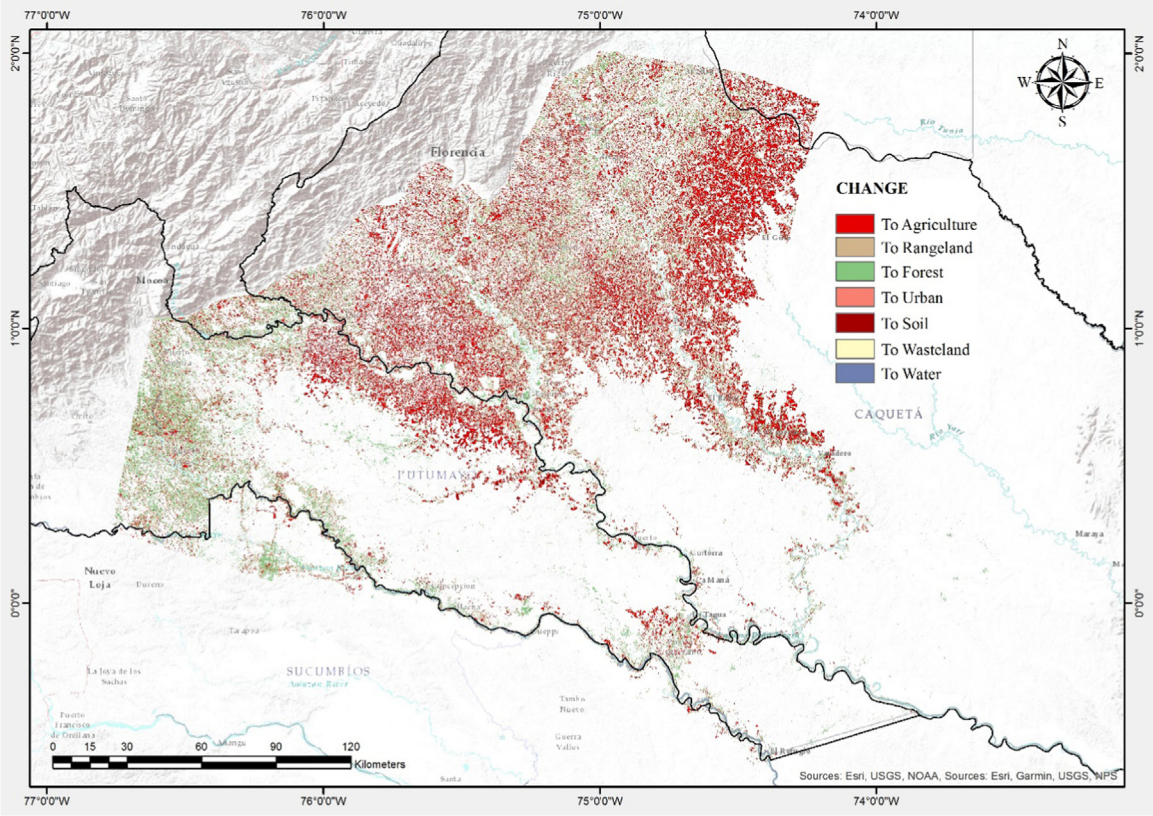

Fig. 6. LULC change detection map from 2000 to 2016 with a terrain basemap as background. The most extensive change of Tropical Rainforest into other LULC classes can be seen in red, highlighting where major deforestation occurred. Political boundaries are shown in black.

Table 5
Cross tabulation matrix. LULC "from – to" change information results between 2000 and 2016.

		2016 (km^2)							
		TR	R	A	W	S	BL	BU	Total
2000 (Km^2)	TR	35,463.57	1293.67	4641.76	56.27	324.69	53.44	0.44	41,833.85
	R	1310.02	918.03	1452.48	37.47	28.33	14.66	0.23	3761.22
	A	1686.44	604.72	7125.81	37.22	54.61	52.29	4.57	9565.67
	W	74.88	23.21	84.53	623.48	3.31	114.10	0.10	923.62
	S	255.65	42.39	358.81	16.79	8.31	28.39	0.64	710.96
	BL	22.01	8.53	130.89	15.42	1.14	8.38	6.18	192.56
	BU	0.35	0.03	1.36	0.03	0.29	0.03	7.99	10.08
	Total	38,812.91	2890.58	13,795.65	786.69	420.68	271.29	15.34	56,997.95

Tropical Rainforest (TR), Rangeland (R), Agriculture (A), Water (W), Soil (S), Barren Land (BL), Built-Up (BU), Clouds (C), Shadows (SW).

show significant deforestation in the period of study, meaning that the vulnerability of the human settlements, especially the town of Puerto Leguízamo located along both rivers, have increased and will continue to increase because of deforestation.

Out of the total of 100 "from-to" change categories, only seven classes are displayed in the LULC change detection map (Fig. 6), in order to reduce the number of categories. Land cover or land use changes into a same category were merged, LULC classes that didn't change and changes related to Clouds or Shadows are not shown.

3.3. Accuracy assessment

In order to improve the accuracy of the LULC area estimates, the mapped areas of the changes of interest (in this case, changes to Agriculture and Tropical Rainforest) were adjusted to eliminate bias attributable to map classification error, and confidence intervals were calculated in order to quantify the sampling variability of the estimated area (Olofsson et al., 2013). Most of our accuracies are similar to the user's and producer's accuracies of 80% or better reported by Hansen et al. (2013) in their time-series analysis of Landsat images in characterizing global forest extent and change. While accuracies in some classes were as low as 60%, the user's accuracies for changes to Tropical Rainforest and Agriculture were high: 95% and 96% respectively. The method suggested by Olofsson et al. (2013) was applied to estimate the error-adjusted total area of deforestation, and gave a result of $6117.21 \pm 368.10\,km^2$, with a confidence interval of 95%. This is smaller than the area calculated from the change map using "pixel count" ($6382.68\,km^2$), but the pixel-count area still falls within the 95% confidence interval of the error-adjusted estimated area. The accuracy measures with their associated uncertainties are shown in Appendix (Tables 6–8).

3.4. Deforestation in the Departments of Caquetá and Putumayo

Our understanding of the causes of land change has advanced significantly in recent years and involves situation-specific interactions among a large number of factors at different spatial and temporal scales (Geist et al., 2006). In Colombia the causes of deforestation are diverse and result from a complex network of environmental, social, economic and political factors that differ in each of the region of the country (Lambin et al., 2001), often boosted by contextual factors such as policies of land occupation and agricultural development, armed conflict, poverty and institutional absence among others ("Coca y Deforestación: Mensajes de acción para la planeación del desarrollo, ", 2017). While deforestation in the Brazilian Amazonia is strongly related to macroeconomic factors, transportation infrastructure and demographic pressures (Fearnside, 2005), in the Colombian Amazonia illegal activities are causing significant deforestation. According to the United Nations Office on Drugs and Crime, coca plantation had been declining in Colombia since 2000, however a 51% increase was reported between 2014 and 2015. This may be related to the belief by farmers that increasing their production of coca would improve their negotiation power during the peace process (UNODC, 2017). Average yearly loss rates for our 16-year study of the Colombian Amazon are higher than estimates from other studies which suggest an annual rate of change of forest cover between − 0.38% (Achard et al., 2014) and − 0.4% in tropical South America (FAO, 2015).

The environmental conflicts occurring in both Caquetá and Putumayo consist mainly of two factors: incompatibility of the current use of the soil in relation to the forest's capacity to sustain it, and overexploitation of resources through different forms of extractivism, without any replenishment or regulation (Montoya, 2000). Both mega-projects and extractivism initiatives have resulted in the contamination of water sources, the exponential increase of deforestation and increased vulnerability to climate change, as deforestation is known to cause increase of surface temperature and changes in rain patterns due to loss of evapotranspiration, and alterations in the carbon cycle (Costa and Foley, 2000; Shukla et al., 1990). Historically, in the Department of Putumayo, there has not been a clear policy of environmental conservation; therefore, extractivism interventions have not taken into account the regional conflicts and needs that aggravate the environmental deterioration (Gobernación del Putumayo, 2016).

4. Conclusions

The economy of the Colombian Amazon region still depends on extensive livestock farming, timber extraction, mining and agricultural production. Consequently, the environmental impacts of these activities, together with other activities such as hunting and commercial fishing, are significant. Additionally, the disorganized concentration of populations across the region due to self-built housing without planning have caused land fragmentation. Based on the high rates of deforestation observed in this study, proper land use management strategies and development plans need to be established and implemented in order help to protect the Amazon rainforest and to avoid further damage in the long-term due to human actions. This will require using the regional variability we observed within each department to help focus future social, economic and ecological studies aimed at improving our understanding of the region-specific driving forces, and identifying possible mitigation strategies. Deforestation inside protected areas should be closely monitored because these are the areas that have been identified as priorities for conservation and our study results show that they are highly vulnerable to the pressures driving deforestation. Illegal activities must be specifically addressed since they may be causing the most important changes and impacts on the region's environment: because they are illicit, they occur disproportionately within protected park land where they can be better hidden.

Given the recent peace process in Colombia marking the official end to the internal armed conflict in 2016, it would be especially interesting to continue tracking deforestation in Putumayo and Caquetá, both of which have been heavily affected by the armed conflict, to see if the rates and patterns of LULC will change in response. Tracking of year-to-

Table 6
Accuracy measures of the supervised classification for the year 2000 with 95% confidence intervals.

ACCURACY MEASURES			
CLASS	**User's Accuracy**	**Producer's Accuracy**	**Overall Accuracy**
TR	0.99 ± 0.01	0.99 ± 0.04	**0.98 ± 0.01**
R	0.90 ± 0.04	0.96 ± 0.03	
A	0.95 ± 0.02	0.96 ± 0.02	
W	0.95 ± 0.03	0.98 ± 0.02	
S	0.92 ± 0.04	0.89 ± 0.03	
BL	0.93 ± 0.04	0.60 ± 0.04	
BU	0.98 ± 0.03	0.64 ± 0.02	
C	0.98 ± 0.02	0.69 ± 0.05	
SW	0.97 ± 0.03	0.72 ± 0.03	

Tropical Rainforest (TR), Rangeland (R), Agriculture (A), Water (W), Soil (S), Barren Land (BL), Built-Up (BU), Clouds (C), Shadows (SW).

Table 7
Accuracy measures of the supervised classification for the year 2016 with 95% confidence intervals.

ACCURACY MEASURES			
CLASS	**User's Accuracy**	**Producer's Accuracy**	**Overall Accuracy**
TR	0.98 ± 0.02	1.00 ± 0.03	**0.97 ± 0.01**
R	0.89 ± 0.04	0.87 ± 0.02	
A	0.98 ± 0.01	0.94 ± 0.02	
W	0.95 ± 0.03	0.97 ± 0.03	
S	0.94 ± 0.03	0.87 ± 0.03	
BL	0.90 ± 0.04	0.74 ± 0.03	
BU	0.96 ± 0.03	0.81 ± 0.02	
C	1.00 ± 0.01	0.97 ± 0.05	
SW	0.97 ± 0.03	0.98 ± 0.01	

Tropical Rainforest (TR), Rangeland (R), Agriculture (A), Water (W), Soil (S), Barren Land (BL), Built-Up (BU), Clouds (C), Shadows (SW).

Table 8
Change detection analysis accuracy measures presented with a 95% confidence interval.

ACCURACY MEASURES			
CHANGE	**User's Accuracy**	**Producer's Accuracy**	**Overall Accuracy**
1	0.95 ± 0.05	0.72 ± 0.02	**0.92 ± 0.02**
2	0.91 ± 0.04	0.99 ± 0.06	
3	0.96 ± 0.05	0.90 ± 0.03	
4	0.97 ± 0.04	0.68 ± 0.05	
5	0.96 ± 0.04	1.00 ± 0.06	
6	0.95 ± 0.04	0.65 ± 0.04	
7	0.95 ± 0.05	0.72 ± 0.03	

To Tropical Rainforest (1), To Rangeland (2), To Agriculture (3), To Water Bodies (4), To Soil (5), To Barren Land (6), To Built-Up (7).

year changes using high-resolution data (where available) would be especially useful for correlating specific economic and political conditions with annual deforestation rates and distributions. We suspect that a reduction in new plantations of illegal crops in national park preserves, and possibly natural reforestation replacing existing crops, may be one result.

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Conflicts of interest

The authors declare no conflict of interest.

Appendix

Accuracy measures with their associated uncertainties for the supervised classifications of both periods and for the change detection analysis. Tables 6–8.

References

Abbas, S., Nichol, J.E., Fischer, G.A., 2016. A 70-year perspective on tropical forest regeneration. Sci. Total Environ. 544, 544–552. https://doi.org/10.1016/j.scitotenv.2015.11.171.

Achard, F., Beuchle, R., Mayaux, P., Stibig, H., Bodart, B., Brink, A., Carboni, S., Desclée, B., Donnay, F., Eva, H.D., Lupi, A., Raši, R., Seliger, R., Simonetti, D., 2014. Determination of tropical deforestation rates and related carbon losses from 1990 to 2010. Glob. Change Biol. 20, 2540–2554. https://doi.org/10.1111/gcb.12605.

Achard, F., DeFries, R., Eva, H., Hansen, M., Mayaux, P., Stibig, H.-J., 2007. Pan-tropical monitoring of deforestation. Environ. Res. Lett. 2, 045022. https://doi.org/10.1088/1748-9326/2/4/045022.

Alves, D.S., 2002. An analysis of the geographical patterns of deforestation in the Brazilian Amazon in the period 1991–1996. Deforest. Land Use Amaz 95–106.

Alves, D.S., Batistella, M., Linhares, C.A., 2009. An analysis of landscape fragmentation in the Brazilian Amazon based on deforestation data derived from Landsat imagery.

Amazon Rainforest, 2015. [WWW Document]. . Greenpeace USA. URL 〈https://www.greenpeace.org/usa/forests/amazon-rainforest/〉 (Accessed 23 March 2018).

Anderson, J.R., 1976. A Land Use and Land Cover Classification System for Use with Remote Sensor Data. U.S. Government Printing Office.

Armenteras, D., Cabrera, E., Rodríguez, N., Retana, J., 2013a. National and regional determinants of tropical deforestation in Colombia. Reg. Environ. Change 13, 1181–1193. https://doi.org/10.1007/s10113-013-0433-7.

Armenteras, D., Cabrera, E., Rodríguez, N., Retana, J., 2013b. National and regional determinants of tropical deforestation in Colombia. Reg. Environ. Change 13, 1181–1193. https://doi.org/10.1007/s10113-013-0433-7.

Armenteras, D., Rudas, G., Rodriguez, N., Sua, S., Romero, M., 2006. Patterns and causes of deforestation in the Colombian Amazon. Ecol. Indic. 6, 353–368. https://doi.org/10.1016/j.ecolind.2005.03.014.

Batistella, M., Brondizio, E.S., Moran, E.F., 2000. Comparative analysis of landscape fragmentation in Rondônia, Brazilian Amazon. Int. Arch. Photogramm. Remote Sens. 33, 148–155.

Bewernick, T., de Tanago Meñaca, J.G., Herold, M., Verbesselt, J., 2015. Mapping Post Deforestation Land Use in the Brazilian Amazon Using Remote Sensing Time Series.

Boucher, D., Elias, P., Lininger, K., May-Tobin, C., Roquemore, S., Saxon, E., 2011. The Root of the Problem: What's Driving Tropical Deforestation Today?.

Butt, A., Shabbir, R., Ahmad, S.S., Aziz, N., 2015. Land use change mapping and analysis using Remote Sensing and GIS: a case study of Simly watershed, Islamabad, Pakistan. Egypt. J. Remote Sens. Space Sci. 18, 251–259. https://doi.org/10.1016/j.ejrs.2015.07.003.

Carreiras, J.M.B., Pereira, J.M.C., Shimabukuro, Y.E., 2006. Land-cover mapping in the brazilian amazon using SPOT-4 vegetation data and machine learning classification methods. Photogramm. Eng. Remote Sens. 72, 897–910. https://doi.org/10.14358/PERS.72.8.897.

Chazdon, R.L., Guariguata, M.R., 2016. Natural regeneration as a tool for large-scale forest restoration in the tropics: prospects and challenges. Biotropica 48, 716–730. https://doi.org/10.1111/btp.12381.

Coca y Deforestación: Mensajes de acción para la planeación del desarrollo, 2017.

Congalton, R.G., 2004. Putting the map back in map accuracy assessment. Remote Sens. GIS Accur. Assess. 1–11.

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., Lambin, E., 2004. Digital change detection methods in ecosystem monitoring: a review. Int. J. Remote Sens. 25, 1565–1596. https://doi.org/10.1080/0143116031000101675.

Corpoamazonia, 2013. [WWW Document]. Clima. URL 〈http://www.corpoamazonia.gov.co/region/Jur_Clima.htm〉. (Accessed 22 November 2017).

Costa, M.H., Foley, J.A., 2000. Combined effects of deforestation and Doubled atmospheric CO_2 concentrations on the climate of Amazonia. J. Clim. 13, 18–34. https://doi.org/10.1175/1520-0442(2000)013<0018:CEODAD>2.0.CO;2.

Curatola Fernández, G.F., Obermeier, W.A., Gerique, A., López Sandoval, M.F., Lehnert, L.W., Thies, B., Bendix, J., 2015. Land cover change in the Andes of Southern Ecuador—patterns and drivers. Remote Sens. 7, 2509–2542. https://doi.org/10.3390/rs70302509.

Dávalos, L.M., Sanchez, K.M., Armenteras, D., 2016. Deforestation and coca cultivation rooted in twentieth-century development projects. BioScience 66, 974–982. https://doi.org/10.1093/biosci/biw118.

Dewan, A.M., Yamaguchi, Y., 2009. Land use and land cover change in greater Dhaka, Bangladesh: using remote sensing to promote sustainable urbanization. Appl. Geogr. 29, 390–401. https://doi.org/10.1016/j.apgeog.2008.12.005.

Duadze, S.E.K., 2004. Land Use and Land Cover Study of the Savannah Ecosystem in the Upper West Region (Ghana) Using Remote Sensing. Cuvillier Verlag.

Etter, A., Mcalpine, C., Phinn, S., Pullar, D., Possingham, H., 2006a. Characterizing a tropical deforestation wave: a dynamic spatial analysis of a deforestation hotspot in the Colombian Amazon. Glob. Change Biol. 12, 1409–1420. https://doi.org/10.1111/j.1365-2486.2006.01168.x.

Etter, A., McAlpine, C., Phinn, S., Pullar, D., Possingham, H., 2006b. Unplanned land clearing of Colombian rainforests: spreading like disease? Landsc. Urban Plan. 77, 240–254. https://doi.org/10.1016/j.landurbplan.2005.03.002.

Etter, A., McAlpine, C., Wilson, K., Phinn, S., Possingham, H., 2006c. Regional patterns of agricultural land use and deforestation in Colombia. Agric. Ecosyst. Environ. 114, 369–386. https://doi.org/10.1016/j.agee.2005.11.013.

FAO, 2015. Global Forest Resources Assessment 2015.

Fearnside, P.M., 2005. Deforestation in Brazilian Amazonia: history, rates, and consequences. Conserv. Biol. 19, 680–688. https://doi.org/10.1111/j.1523-1739.2005.00697.x.

Geist, H., McConnell, W., Lambin, E.F., Moran, E., Alves, D., Rudel, T., 2006. Causes and Trajectories of Land-Use/Cover Change. In: Land-Use and Land-Cover Change. Springer, Berlin, Heidelberg, pp. 41–70. https://doi.org/10.1007/3-540-32202-7_3.

Geosystems, L., 2005. ERDAS Field Guide. Norcross Ga. Leica Geosystems Geospatial Imaging LLC.

Gobernación de Caquetá, 2017. [WWW Document]. Hist. Caquetá. URL 〈http://www.caqueta.gov.co/departamento/historia-del-caqueta〉. (Accessed 16 October 2017).

Gobernación de Putumayo, 2017. [WWW Document]. Inf. Gen. URL 〈https://www.putumayo.gov.co/informacion-general.html〉. (Accessed 10 October 2017).

Gobernación del Caquetá, 2016. Plan de Desarrollo Departamental del Caquetá: Plan De Desarrollo Con Usted Hacemos Mas Por El Caquetá 2016–2019.

Gobernación del Putumayo, 2016. Plan de Desarrollo Departamental: Putumayo territorio de paz, biodiverso y ancestral.

Grainger, A., 1996. An Evaluation of the FAO tropical forest resource assessment, 1990. Geogr. J. 162, 73–79. https://doi.org/10.2307/3060217.

Grinand, C., Rakotomalala, F., Gond, V., Vaudry, R., Bernoux, M., Vieilledent, G., 2013. Estimating deforestation in tropical humid and dry forests in Madagascar from 2000 to 2010 using multi-date Landsat satellite images and the random forests classifier. Remote Sens. Environ. 139, 68–80. https://doi.org/10.1016/j.rse.2013.07.008.

Guild, L.S., Cohen, W.B., Kauffman, J.B., 2004. Detection of deforestation and land conversion in Rondônia, Brazil using change detection techniques. Int. J. Remote Sens. 25, 731–750. https://doi.org/10.1080/0143116031000159935.

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-resolution global maps of 21st-century forest cover change. Science 342, 850–853. https://doi.org/10.1126/science.1244693.

Hansen, M.C., Stehman, S.V., Potapov, P.V., Arunarwati, B., Stolle, F., Pittman, K., 2009. Quantifying changes in the rates of forest clearing in Indonesia from 1990 to 2005 using remotely sensed data sets. Environ. Res. Lett. 4, 034001. https://doi.org/10.1088/1748-9326/4/3/034001.

Hecheltjen, A., Thonfeld, F., Menz, G., 2014. Recent Advances in Remote Sensing Change Detection – A Review. In: Land Use and Land Cover Mapping in Europe, Remote Sensing and Digital Image Processing. Springer, Dordrecht, pp. 145–178. https://doi.org/10.1007/978-94-007-7969-3_10.

IDEAM, 2014. Atlas climatológico de Colombia [WWW Document]. URL 〈http://www.ideam.gov.co/web/tiempo-y-clima/atlas#_48_INSTANCE_xoDpvO7rhD5O_%3Dhttp%253A%252F%252Fwww.ideam.gov.co%252FAtlasWeb%252Findex.html%253F〉 (Accessed 19 June 2018).

IDEAM, 2002. Primera Generación de Indicadores de la Línea Base de la Información Ambiental de Colombia.

Jia, Y., Tang, L., Wang, L., 2017. Influence of ecological factors on estimation of impervious surface area using landsat 8 imagery. Remote Sens. 9, 751. https://doi.org/10.3390/rs9070751.

Kim, D.-H., Sexton, J.O., Townshend, J.R., 2015. Accelerated deforestation in the humid tropics from the 1990s to the 2000s. Geophys. Res. Lett. 42. https://doi.org/10.1002/2014GL062777.

Knudby, A., Nordlund, L.M., Palmqvist, G., Wikström, K., Koliji, A., Lindborg, R., Gullström, M., 2014. Using multiple Landsat scenes in an ensemble classifier reduces classification error in a stable nearshore environment. Int. J. Appl. Earth Obs. Geoinf. 28, 90–101. https://doi.org/10.1016/j.jag.2013.11.015.

Lambin, E.F., Geist, H.J., Lepers, E., 2003. Dynamics of land-use and land-cover change in tropical regions. Annu. Rev. Environ. Resour. 28, 205–241. https://doi.org/10.1146/annurev.energy.28.050302.105459.

Lambin, E.F., Turner, B.L., Geist, H.J., Agbola, S.B., Angelsen, A., Bruce, J.W., Coomes, O.T., Dirzo, R., Fischer, G., Folke, C., George, P.S., Homewood, K., Imbernon, J., Leemans, R., Li, X., Moran, E.F., Mortimore, M., Ramakrishnan, P.S., Richards, J.F., Skånes, H., Steffen, W., Stone, G.D., Svedin, U., Veldkamp, T.A., Vogel, C., Xu, J., 2001. The causes of land-use and land-cover change: moving beyond the myths. Glob. Environ. Change 11, 261–269. https://doi.org/10.1016/S0959-3780(01)00007-3.

Leonel, C., 2016. Parar la deforestacion en el Putumayo, una necesidad y un reto para todos. Magazín Inf. Digit. Putumayo.

Lewis, S.L., Edwards, D.P., Galbraith, D., 2015. Increasing human dominance of tropical forests. Science 349, 827–832. https://doi.org/10.1126/science.aaa9932.

Li, C., Wang, J., Wang, L., Hu, L., Gong, P., 2014. Comparison of classification algorithms and training sample sizes in urban land classification with landsat thematic mapper imagery. Remote Sens. 6, 964–983. https://doi.org/10.3390/rs6020964.

Li, G., Lu, D., Moran, E., Hetrick, S., 2011. Land-cover classification in a moist tropical region of Brazil with Landsat thematic Mapper imagery. Int. J. Remote Sens. 32, 8207–8230. https://doi.org/10.1080/01431161.2010.532831.

Linares, J.R., Cárdenas, W., Baquero, C., 2007. Cambio de la cobertura boscosa como sucedáneo de la dinámica colonizadora en el Departamento del Caquetá, 1986-20001. Rev. Investig. 7, 95–104.

Locklin, C.C., Haack, B., 2003. Roadside measurements of deforestation in the Amazon area of Bolivia. Environ. Manag. 31, 774–783. https://doi.org/10.1007/s00267-002-2867-4.

Lu, D., Batistella, M., Li, G., Moran, E., Hetrick, S., Freitas, C., da, C., Dutra, L.V., Sant'Anna, S.J.S., 2012. Land use/cover classification in the Brazilian Amazon using satellite images. Pesqui. Agropecuária Bras. 47, 1185–1208. https://doi.org/10.1590/S0100-204×2012000900004.

Lu, D., Li, G., Moran, E., Hetrick, S., 2013. Vegetation change detection in the Brazilian Amazon with Multitemporal Landsat images. Remote Sens. Nat. Resour. 127–140.

Manandhar, R., Odeh, I.O.A., Ancev, T., 2009. Improving the accuracy of land use and land cover classification of landsat data using post-classification enhancement. Remote Sens. 1, 330–344. https://doi.org/10.3390/rs1030330.

Margono, B.A., Turubanova, S., Zhuravleva, I., Potapov, P., Alexandra, Tyukavina, Baccini, A., Goetz, S., Hansen, M.C., 2012. Mapping and monitoring deforestation

and forest degradation in Sumatra (Indonesia) using Landsat time series data sets from 1990 to 2010. Environ. Res. Lett. 7, 034010. https://doi.org/10.1088/1748-9326/7/3/034010.

Marsik, M., Stevens, F.R., Southworth, J., 2011. Amazon deforestation: rates and patterns of land cover change and fragmentation in Pando, northern Bolivia, 1986 to 2005. Prog. Phys. Geogr. Earth Environ. 35, 353–374. https://doi.org/10.1177/0309133311399492.

Matthews, E., 2001. Understanding the FRA 2000. Oceania 88, 129.

Messina, J.P., Delamater, P.L., 2006. Defoliation and the war on drugs in Putumayo, Colombia. Int. J. Remote Sens. 27, 121–128. https://doi.org/10.1080/01431160500293708.

Ministerio de Ambiente y Desarrollo Sostenible, 2015. Plan Nacional de Restauración Ecológica, Rehabilitación y Recuperación de Áreas Degradadas.

Montoya, C., 2000. Municipio de Leguizamo. Plan De Ordenamiento Territorial.

Oliveira, P.J.C., Asner, G.P., Knapp, D.E., Almeyda, A., Galván-Gildemeister, R., Keene, S., Raybin, R.F., Smith, R.C., 2007. Land-use allocation protects the Peruvian Amazon. Science 317, 1233–1236. https://doi.org/10.1126/science.1146324.

Olofsson, P., Foody, G.M., Stehman, S.V., Woodcock, C.E., 2013. Making better use of accuracy data in land change studies: estimating accuracy and area and quantifying uncertainty using stratified estimation. Remote Sens. Environ. 129, 122–131. https://doi.org/10.1016/j.rse.2012.10.031.

Peel, M.C., Finlayson, B.L., Mcmahon, T.A., 2007. Updated world map of the Köppen-Geiger climate classification. Hydrol. Earth Syst. Sci. Discuss. 4, 439–473.

Perz, S.G., Aramburú, C., Bremner, J., 2005. Population, land use and deforestation in the Pan Amazon Basin: a comparison of Brazil, Bolivia, Colombia, Ecuador, Perú and Venezuela. Environ. Dev. Sustain. 7, 23–49. https://doi.org/10.1007/s10668-003-6977-9.

Pontius Jr, R.G., Millones, M., 2011. Death to kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. Int. J. Remote Sens. 32, 4407–4429. https://doi.org/10.1080/01431161.2011.552923.

Ramankutty, N., Amato, T., E., Monfreda, C., Foley, J.A., 2008. Farming the planet: 1.Geographic distribution of global agricultural lands in the year 2000. Glob. Biogeochem. Cycles 22. https://doi.org/10.1029/2007GB002952.

Rawat, J.S., Kumar, M., 2015. Monitoring land use/cover change using remote sensing and GIS techniques: a case study of Hawalbagh block, district Almora, Uttarakhand, India. Egypt. J. Remote Sens. Space Sci. 18, 77–84. https://doi.org/10.1016/j.ejrs.2015.02.002.

Reyes, M.C., 2017. Evaluación de la deforestación en las sabanas del Yarí a partir de un análisis multitemporal de imágenes de satélite Landsat años 2010 y 2017 por medio del procesamiento digital de imágenes (B.S. thesis). Universidad Militar Nueva Granada.

Riaño Umbarila, E., Duarte, V., Júnior, R.S., 2007. Aplicación de la metodología de PRODES digital y detalle de su leyenda en área de la frontera Leticia (Colombia)-Tabatinga (Brasil). Perspect. Geogr. 13.

Rocha-Santos, L., Pessoa, M.S., Cassano, C.R., Talora, D.C., Orihuela, R.L.L., Mariano-Neto, E., Morante-Filho, J.C., Faria, D., Cazetta, E., 2016. The shrinkage of a forest: landscape-scale deforestation leading to overall changes in local forest structure. Biol. Conserv. 196, 1–9. https://doi.org/10.1016/j.biocon.2016.01.028.

Ruiz, J., 1989. Desarrollo regional en Colombia: ordenamiento ambiental y desarrollo regional. Cuad. Ind. Econ. Rural 22.

Ruiz, J., Cárdenas, W., Baquero, C., 2011. Deforestación y Dinámica del Bosque Secundario en la Amazonia Colombiana 1986–2000. Rev. Acad. Colomb. Cienc. Exactas Físicas Nat. 35, 531–545.

Salovaara, K.J., Thessler, S., Malik, R.N., Tuomisto, H., 2005. Classification of Amazonian primary rain forest vegetation using Landsat ETM+ satellite imagery. Remote Sens. Environ. 97, 39–51. https://doi.org/10.1016/j.rse.2005.04.013.

Santos, F., Dubovyk, O., Menz, G., 2017. Monitoring forest dynamics in the Andean Amazon: the applicability of breakpoint detection methods using landsat time-series and genetic algorithms. Remote Sens. 9, 68. https://doi.org/10.3390/rs9010068.

Shimabukuro, Y.E., Duarte, V., Santos, J.R. dos, Batista, G.T., 2000. Mapping and monitoring deforestation areas in Amazon region using semi-automatic classification of Landsat Thematic Mapper images, In: IGARSS 2000. IEEE 2000 International Geoscience and Remote Sensing Symposium. Taking the Pulse of the Planet: The Role of Remote Sensing in Managing the Environment. Proceedings (Cat. No.00CH37120). Presented at the IGARSS 2000. IEEE 2000 International Geoscience and Remote Sensing Symposium. Taking the Pulse of the Planet: The Role of Remote Sensing in Managing the Environment. Proceedings (Cat. No.00CH37120), pp. 1999–2001 vol. 5. ⟨https://doi.org/10.1109/IGARSS.2000.858226⟩.

Shukla, J., Nobre, C., Sellers, P., 1990. Amazon deforestation and climate change. Science 247, 1322–1325. https://doi.org/10.1126/science.247.4948.1322.

Sierra, R., 2000. Dynamics and patterns of deforestation in the western Amazon: the Napo deforestation front, 1986–1996. Appl. Geogr. 20, 1–16. https://doi.org/10.1016/S0143-6228(99)00014-4.

Song, C., Woodcock, C.E., Seto, K.C., Lenney, M.P., Macomber, S.A., 2001. Classification and change detection using Landsat TM data: When and How to correct atmospheric effects? Remote Sens. Environ. 75, 230–244. https://doi.org/10.1016/S0034-4257(00)00169-3.

Souza, C., Firestone, L., Silva, L.M., Roberts, D., 2003. Mapping forest degradation in the Eastern Amazon from SPOT 4 through spectral mixture models. Remote Sens. Environ., Large Scale Biosphere Atmosphere Experiment in Amazonia 87, 494–506. ⟨https://doi.org/10.1016/j.rse.2002.08.002⟩.

Souza, J., Siqueira, J.V., Sales, M.H., Fonseca, A.V., Ribeiro, J.G., Numata, I., Cochrane, M.A., Barber, C.P., Roberts, D.A., Barlow, J., 2013. Ten-year Landsat classification of deforestation and forest degradation in the Brazilian Amazon. Remote Sens. 5, 5493–5513. https://doi.org/10.3390/rs5115493.

Stabursvik, E.M., 2007. The challenge of identifying and conserving valuable ecosystems close to human settlements in a northern area. An approach based on field- and satellite data.

UNODC, 2017. Colombia: Survey of territories affected by illicit crops – 2016.

Viña, A., Echavarria, F.R., Rundquist, D.C., 2004. Satellite change detection analysis of deforestation rates and patterns along the Colombia – Ecuador border. AMBIO J. Hum. Environ. 33, 118–125. https://doi.org/10.1579/0044-7447-33.3.118.

Wilson, K., Newton, A., Echeverría, C., Weston, C., Burgman, M., 2005. A vulnerability analysis of the temperate forests of south central Chile. Biol. Conserv. 122, 9–21. https://doi.org/10.1016/j.biocon.2004.06.015.

Yuan, F., Sawaya, K.E., Loeffelholz, B.C., Bauer, M.E., 2005. Land cover classification and change analysis of the twin cities (Minnesota) metropolitan area by multitemporal Landsat remote sensing. Remote Sens. Environ. 98, 317–328. https://doi.org/10.1016/j.rse.2005.08.006.

Zuleta, A.M.P., 2015. Estudio Multitemporal de la Deforestación en Colombia Utilizando Procesamiento de Imágenes. Rev. Ingenio UFPSO 8, 159–175.